Dropping Out of University in Response to the COVID-19 Pandemic

Etienne Dagorn et Léonard Moulin

DOCUMENTS DE TRAVAIL 276

Dropping Out of University in Response to the COVID-19 Pandemic

Etienne Dagorn, Léonard Moulin

Octobre 2023

Dropping Out of University in Response to the COVID-19 Pandemic

Etienne Dagorn* Léonard Moulin†

October 20, 2023

Abstract

This study empirically examines the impact of the COVID-19 pandemic on university students' enrollment behaviors using a comprehensive database of university enrollments from 2012 to 2021. Our analysis reveals a 10.6% decline in the probability of re-enrollment for the subsequent academic year among the cohort affected by the pandemic. In particular, this effect is particularly pronounced among students pursuing STEM tracks and male students. To further investigate the underlying mechanisms, we employ a natural experiment framework in France, leveraging regional variations in policies adopted in response to the spread of the disease. Our results do not provide convincing evidence that stricter measures had an impact on student re-enrollment or on the likelihood of graduation. These findings contribute to our understanding of the disruptive consequences of the COVID-19 pandemic on students' educational trajectories and highlight the importance of considering policy responses to mitigate adverse effects on educational outcomes.

JEL codes: I23, I24, J24, I18.

Keywords: COVID-19, student, drop-out, graduation, university.

*Institut national d'études démographiques (INED), F-93300 Aubervilliers, France. E-mail: etienne.dagorn@ined.fr.

†Institut national d'études démographiques (INED), F-93300 Aubervilliers, France. E-mail: leonard.moulin@ined.fr.

1 Introduction

Each year, students face a critical decision regarding their higher education, as they weigh opportunity costs against anticipated labor market benefits. This decision is closely linked to students' perceptions of labor market outcomes, which are significantly influenced by external shocks such as financial crises, business cycles, and pandemics (Adamopoulou and Tanzi, 2017; Aucejo et al., 2020; Blom, Cadena, and Keys, 2021). Examining the impact of such extreme events on students' educational trajectories is crucial because they often exacerbate existing societal inequalities (Atkinson and Morelli, 2011; Stantcheva, 2022). The COVID-19 pandemic provides an ideal context to investigate this issue, given its profound and likely enduring effects on educational outcomes, including learning (Werner and Woessmann, 2021; Svaleryd and Vlachos, 2022; Betthäuser, Bach-Mortensen, and Engzell, 2023). However, the extent to which the pandemic has affected students' enrollment decisions remains largely unexplored.

This study aims to examine the impact of the COVID-19 pandemic on university student dropout rates in France by analyzing changes in patterns of re-enrollment for the 2020-2021 academic year. We hypothesize that external shocks like the pandemic may increase the likelihood of university student dropout. Using comprehensive administrative data on student enrollment status from 2012 to 2021, we investigate the enrollment decisions of 4,867,940 university students, representing 12,515,064 choices. Our findings indicate that the COVID-19 cohort showed a decreased propensity for re-enrollment in the subsequent academic year, with significant variations across fields of study and student socioeconomic characteristics. We then make use of the French institutional context, which provides a natural experiment, to document the extent to which policy stringency influenced students' decision to continue their education. We do not observe evidence that heightened lockdown impacted student enrollment behaviors. Finally, we use highly disaggregated geographical units to examine two possible mechanisms behind changes in student enrollment behaviors: direct exposure to the pandemic and labor market opportunities. Our findings indicate that a higher unemployment rate is correlated with a greater likelihood of graduating.

Our data have several distinct characteristics that enable us to investigate the impact of the COVID-19 pandemic on university students' re-enrollment decisions while considering a wide range of individual factors. First, our data comprehensively capture students' enrollment choices from 2012 to 2021, allowing us to track student trajectories within the French higher education system in detail. Second, our data allow us to distinguish between changes in grading practices and individual decisions to discontinue studies at higher education institutions. Third, our data include information on both students' geographical locations and local variations in COVID-19 transmission rates, which we use to examine the potential impact of local pandemic conditions on dropout rates. The administrative features of our data allow us to measure dropout and attainment in three distinct ways: enrollment for the following academic year, graduation and presence for at least one exam during the academic year. These data collectively provide an unbiased measure of enrollment at the individual student level.

We focus in this paper on the French context, which offers a favorable institutional setting for investigating the relationship between dropout rates and exposure to the COVID-19 pandemic. First, the relatively low cost of university study allows us to closely examine how students react to the pandemic, as their decision-making is not strongly influenced by financial investments in tertiary education. Second, the government's response to the initial wave of the COVID-19 pandemic in France closely resembles that of other Western countries, particularly in terms of transitioning to online instruction for all students. Third, the French institutional context provides an opportunity to examine the causal impact of pandemic lockdown policies on student dropout, a feature that, to the best of our knowledge, has not been explored in the literature. Finally, in our investigation of the spatial distribution of student dropout, we employ a fine-grained geographical unit of analysis, which allows us to access detailed measurements of the unemployment rate and the severity of the pandemic.

Our initial findings provide compelling evidence that the first cohort affected by the COVID-19 pandemic was less likely to re-enroll for the subsequent academic year. Specifically, we observe a 10.6% decrease in the probability of re-enrollment of the COVID-19 cohort compared to the cohort from the previous year. To put this decline into perspective, it is equivalent to the cumulative decline in re-enrollment observed in French higher education institutions over the preceding decade. Furthermore, our analysis reveals significant variability in individual decisions to discontinue studies, which is associated with demographic characteristics and field of study. To provide a more comprehensive understanding of enrollment patterns, we replicate this analysis using alternative outcome measures: likelihood to graduate, and attendance at least one exam during the year. Our results indicate that undergraduate students in the COVID-19 cohort were less likely to graduate, while the pandemic did not affect graduate students' probability of graduating. We do not find any overall effect on exam attendance, which indicates that our main results are not driven by absenteeism. Our results demonstrate that the decrease in dropout rates cannot solely be attributed to changes in grading practices or attendance at final exams.

Our second set of findings uncovers significant variations with student demographics and degree levels (undergraduate vs. graduate studies). Leveraging comprehensive individual enrollment data spanning the last decade, we conduct detailed pre-trends analysis on individual demographics, enabling us to document the relationship between these characteristics and enrollment behaviors during the pandemic. Specifically, we observe a higher likelihood of dropout among male compared to female students. Undergraduate students exhibit an increased probability of dropout, while we find no effect for master's and PhD students. Notably, first- and second-year undergraduate students were most affected by the pandemic, with their likelihood of re-enrollment decreasing by more 20.9% and 17.3%, respectively compared to the previous year. We also observe a stronger effect of COVID-19 for students enrolling in hard-STEM fields (11% for hard-STEM students compared to 10% for non-STEM students).

To gain a deeper understanding of the impact of policies aimed at containing the spread of the virus on university students, we leverage a natural experiment that occurred in France at the end of the first lockdown period. During this time, different regions in the western and eastern parts of the country were subjected to varying levels of policy stringency (e.g. restrictions on social gatherings and movement). Our institutional framework allows us to test the hypothesis that an increase in lockdown policies is negatively related to educational outcomes. Overall, we find that this institutional setting did not have a significant average effect on individual enrollment behaviors. This absence of evidence may seem surprising. It is important to note, however, that the measures implemented during this extension of lockdown were less severe than those in force during the initial lockdown period. Their impact on students' decision to drop out of university may thus have been more limited, resulting in a lack of significant effect on the likelihood of re-enrollment.

We investigate the mechanisms that may explain students' enrollment behaviors. Specifically, we examine two potential factors: the local severity of the pandemic and labor market opportunities for students. The first is based on the intuition that students who are either personally at higher risk of contracting the virus or who have relatives in a similar position may bear a significant mental burden due to the pandemic. We measure local exposure at a detailed geographical level by examining excess mortality over the course of the pandemic, which avoids traditional measurement errors associated with variable testing capacity. The second line of investigation is based on the human capital investment approach, which looks at inter-temporal trade-offs between labor market costs and opportunities. The COVID-19 pandemic brought about significant changes in the labor market, which might have influenced students' tendency to enter the labor force rather than re-enrolling in university. We find little evidence that supports the idea that either mechanism explains students' decision to re-enroll. However, we find a sizeable positive correlation between labor market opportunities and likelihood of graduating.

This paper draws upon three distinct literatures to contribute to the ongoing examination of the impact of COVID-19 on educational outcomes. First, it examines the effects of school closures on learning outcomes, a topic that has been extensively studied across various countries, revealing significant learning losses (see Betthäuser, Bach-Mortensen, and Engzell (2023) for an extensive review of the literature). Underprivileged students, who have limited access to educational resources for remote learning, have disproportionately borne the brunt of the COVID-19 period (Grewenig et al., 2021; Werner and Woessmann, 2021). Second, the paper investigates the pandemic's impact on students' perceptions of returning to education and their subsequent choices. An increasing body of evidence suggests that the pandemic has influenced not only students' learning but also their decision-making regarding their educational paths (Aucejo et al., 2020; Aalto, Müller, and Tilley, 2022). For instance, Aalto, Müller, and Tilley (2022) find that the pandemic has decreased the likelihood of high school applicants in Sweden applying to top-ranked vocational programs. Given these findings, it is reasonable to anticipate that the pandemic may also have influenced university students' decisions to continue their enrollment in university. They may have faced increased financial stress in comparison to high school students and experienced disruptions in their educational journey.

The need to balance the pursuit of higher income through the acquisition of more human capital with the opportunity cost of forgoing participation in the labor market during a specific period introduces uncertainty regarding the impact of economic shocks on education (Ferreira and Schady, 2009).[1] According to a recent survey by Wachter (2020), university students' incomes after leaving education exhibit high sensitivity to economic fluctuations. College students leaving their studies without graduating during a recession earn 10% less on average over the ten years after leaving education. While many studies have examined relationships between traditional demographic factors and university enrollment (Montmarquette, Mahseredjian, and Houle, 2001; Gury, 2011; Aina et al., 2018), this paper specifically focuses on exploring the impact of these demographics on university dropout in times of ambiguity in both health and economic domains. In the context of the COVID-19 pandemic, students faced i) significant financial constraints and ii) the mental burden of both online learning and labor market downturns. Various studies highlight the negative impacts of the COVID-19 pandemic (Bulman and Fairlie, 2022; Schanzenbach and Turner, 2022), such as the decline in enrollment at U.S. community colleges by 11% and 9.5% between 2019 and 2020, respectively. [2] This paper extends their findings to offer a comprehensive analysis focused on university students, particularly examining how lockdown policies' stringency influences their enrollment behaviors.

Third, the paper contributes to the literature documenting the impact of COVID-19 on inequalities. Stantcheva (2022) provides an overview of the impact of the pandemic on economic and social inequalities, examining four main dimensions of interest: inequalities across the income distribution, inequalities across sectors and regions, gender inequalities, and educational inequalities. Converging evidence shows that the pandemic and the associated economic policies have accentuated existing inequalities in most of these do-

[1] For example, Bulman, Fairlie, et al., 2021 demonstrate that income shocks induced by a lottery have a positive effect on school attendance, while Dang et al., 2022 show that these shocks affect expenditure on children's education.

[2] Looking at students before they enter tertiary education, Schueler and Miller, 2023 find that pre-K–12 enrollment dropped by 4% between fall 2019 and fall of 2020.

mains. In terms of education, studies show that school closures exacerbated pre-existing learning inequalities along dimensions such as wealth, urbanicity, gender, and children's ability to study from home (Andrew et al., 2020; Agostinelli et al., 2022; Parolin and Lee, 2021). Reducing inequalities among university students is crucial for addressing disparities in the labor market, especially among women and minorities who experience limited economic opportunities post-graduation and were disproportionately affected by the pandemic.

The rest of the document is organized as follows. Section 2 provides some institutional background on French higher education settings as well as information on the evolving policy response to COVID-19 in France during the study period. Section 3 describes the data and the construction of our main variables, along with some descriptive statistics on our main variables of interest. Section 4 presents our empirical approaches, detailing our identification strategies, their underlying assumptions, and how we test our hypotheses. Section 5 presents our results on the relationship between the effects of the local intensity of the COVID-19 pandemic and university dropout, and Section 6 concludes.

2 Institutional Background

This section provides the French higher education system as well as the policy response to COVID-19 implemented during the 2019-2020 academic year.

2.1 French Higher Education System

At the end of upper secondary school, French students take a national exam called the "*baccalauréat*", and those who pass it are eligible to apply for tertiary education. The French higher education system includes three different types of post-secondary programs, two selective and one non-selective. While the "*Licence*" (undergraduate degree) at universities is mainly non-selective and is open to all high school graduates, other programs, such as two-year vocational programs ("*Sections de Techniciens Supérieurs*"), and "*Classes Préparatoire aux Grandes Ecoles*," are selective.[3] Because it is a largely non-selective sector, we focus on students enrolled in a university degree program. University is the most popular higher education track for secondary students in France, with 60% of those who obtain their "*baccalauréat*" opting to enter university[4]

Two main features make the higher education system in France a particularly suitable institutional context for investigating the possible exacerbation of educational inequali-

[3] *Classes Préparatoire aux Grandes Ecoles* are among the most prestigious and selective post-secondary programs. Their focus is on preparing students to take the entry exams for the most competitive higher education institutions, the "*Grandes Ecoles*". The "*baccalauréat*" is the French national exam at the end of upper secondary education.

[4] https://publication.enseignementsup-recherche.gouv.fr/eesr/FR/T943/l_acces_a_l_enseignement_superieur/

ties by the COVID-19 pandemic. First, the overwhelming majority (84%) of students are enrolled in tuition-free public institutions, where the average annual fee for enrollment as an undergraduate at a public university was 170 euros as of 2021-2022 (*Tuition Fees in France* 2022). In contrast to the situation in the U.S., where higher education costs can significantly influence students' decision-making, the relatively low cost of studying at a university in France allows us to closely examine how students respond to the pandemic without this added financial burden. Second, although public universities in France are mainly tuition-free (Moulin, Flacher, and Harari-Kermadec, 2016), individuals' access to prestigious academic programs is heavily influenced by their social and economic background (Bonneau, Charrousset, et al., 2021; Bonneau and Grobon, 2022).[5]

2.2 French Policy Response to the COVID-19 in Terms of Education

The COVID-19 pandemic compelled governments around the world to implement stringent measures to curb the transmission of the virus. The closure of schools and universities is among the most severe policies enacted in this period. A majority of Western countries implemented it in the initial phase of the pandemic, France included. Figure 1 illustrates the timeline of policy responses in France. On March 17th, President Emmanuel Macron declared a nationwide lockdown, initially for a duration of two weeks, which was subsequently extended to eight weeks until May 11th. Following this, from May 11th to June 15th, the government adopted a regional approach, selectively relaxing lockdown measures based on the local prevalence of the virus. Consequently, varying levels of policy stringency were observed between eastern France and the rest of the country. In Section 4.2, we explore these regional disparities in greater detail.

National political guidelines played a crucial role in determining the opening and closure of universities during the COVID-19 pandemic. Specifically, regardless of their level of exposure to the virus, all universities were mandated to close from May 11th until the summer break. This uniform national policy ensured a standardized teaching format for all tertiary education students during the 2019-2020 academic year, allowing the effects of COVID-19 policies to be comprehensively evaluated. It is important to note, however, that the quality of teaching may vary depending on the technical skills of instructors and their effectiveness in a distance education situation (Dincher and Wagner, 2021).

[5] More specifically, Bonneau and Grobon (2022) shows that on average, a 10 percentile rank increase in parental income distribution is associated with a 5.8 percentage point rise in the proportion of children accessing higher education. This effect is stronger for children in the top half of the income distribution. Interestingly, they find that the overall level of inequality in this context is similar to that observed in the United States.

3 Data, Measures and Descriptive Statistics

We seek to investigate the influence of COVID-19 and the associated policy and economic conditions on university students' dropout rates by analyzing comprehensive enrollment data. To do so, we require data capturing variations in COVID-19 exposure both across different academic years and within specific cohorts. In Section 3.1, we present the main measures used in the paper, based on records of all students' enrollment in public universities in France. Appendix A presents the comprehensive sources of information used in this paper. By integrating multiple administrative data sources, our analysis aims to determine whether the pandemic and its localized impacts directly affected university dropout rates. Section 3.2 presents the descriptive statistics for each of the cohorts under study.

3.1 Data and Measures

We use a comprehensive dataset on university enrollment to obtain our primary information. The dataset we employ is derived from the "*Système d'Information sur le Suivi de l'Etudiant*" (student information system, or SISE), which is managed by the Statistical Office of the French Ministry of Higher Education. This dataset provides us with individual administrative data on the enrollment status of all students from 2012 to 2021. To avoid duplication, in cases where students were concurrently enrolled in multiple degrees, we consider only one degree per student per year.[6]

Our analysis relies on observable indicators of student dropout, which are derived from the university's enrollment register. The primary measure of interest is a binary variable indicating whether a student remains enrolled at the university in the subsequent academic year. We also examine whether students successfully obtain their degree in the expected graduation year (e.g. third year of university studies for a bachelor's degree, and fifth year of university studies for a master's degree). We also use a binary indicator of students' attendance for at least one final exam. These measures are exclusively drawn from the administrative register, ensuring their objectivity and lack of bias. However, it is important to note that once students discontinue their enrollment, we lack precise information on their subsequent trajectories, such as their entry into the labor market or their choice to live with their parents.

There are several limitations associated with our measure of school dropout, which we briefly address here. First, we are unable to track potential changes in the grading system or exam difficulty, which could influence the passing rate. It is likely that universities, heavily impacted by the pandemic, implemented more lenient exams. To mitigate this limitation, we rely on enrollment decisions in the subsequent year rather than exam

[6] This situation concerns 9.11% of the baseline number of observations from the raw dataset.

scores. Additionally, it is increasingly common for students to participate in international programs such as Erasmus. Travel restrictions during the COVID-19 pandemic had a major impact on student mobility, which could lead to a bias in our analysis. To address this issue, we perform an analysis excluding observations of foreign students who are not enrolled in an exchange year B.2.

3.2 Descriptive Statistics

Table 1 presents the average demographic characteristics of students enrolled in university in the period 2012-2019, and compares them to those of students enrolled in university in the first year of the COVID-19 pandemic. These descriptive statistics show that the difference between cohorts is small (albeit statistically significant, due to the large sample size), ruling out a possible bias in our analysis due to changes in the distribution of student characteristics.

4 Empirical Approach

Section 4.1 presents our main empirical approach. Section 4.2 describes the quasi-natural experiment in differential policy stringency during the first wave of COVID-19.

4.1 Exposure to COVID-19 and Drop-out

We first estimate the probability of being enrolled in a university for the following year using a logit model. Our dependent variable, y_{ijt}, is a dummy variable equals to 1 if the individual i enrolled at the university j in $t-1$ re-enrolls in year t, and equal to 0 if individual i is enrolled in year $t-1$ but does not re-enroll in year t. We estimate the following specification:

$$y_{ijt} = \alpha + \sum_{\substack{t=2013 \\ t \neq 2019}}^{2020} \beta_t \text{year}_t + \mathbf{X}_i' \delta + \Theta_j + \epsilon_{it} \tag{1}$$

The primary focus of this study is the variable of interest, year_t, with $t = 2020$. This variable measures the probability of re-enrollment for the subsequent academic year in 2020 relative to 2019. The vector $\mathbf{X}_i'$ comprises individual-level controls (gender, free lunch status, SES, nationality), Θ_j represents university fixed effects, and ϵ_{it} is the error term clustered at the university level. To analyze the heterogeneity of our effects, i) we consider the effect for each year of study, and ii) we follow previous studies in constructing an aggregate measure of area of study with three values: humanities, soft-STEM (biology, medicine), and hard-STEM (see Charousset and Monnet, 2022).

4.2 Policies Stringency and University Drop-out: Quasi-experimental Evidence

Our first approach allowed us to quantify the overall change in re-enrollment behaviors among university students without regard to differences in the policies implemented to contain the spread of the virus. We now take advantage of a quasi-natural experiment in France to test the hypothesis that lockdown regimes of differing stringency will differentially impact enrollment rates. The French government created a quasi-natural experiment by classifying areas as either "red" or "green" based on the number of recorded COVID-19 cases at the end of the first lockdown. This quasi-experimental setup offers a unique opportunity to compare dropout behaviors between two regions of France that share similar characteristics but experienced different policies. Specifically, a significant number of gathering places (restaurants, cinemas, beaches, large shopping centers, parks and gardens) and educational establishments (nursery and secondary schools) were closed for several weeks following the initial lockdown. Importantly, the decision to implement these policies was not based on educational outcomes, as the primary criterion for implementing additional policies was the prevalence of the virus at the end of the initial lockdown. Appendix B.3 shows the distribution of population characteristics across time and zones.

To estimate the causal impact of lockdown on dropout behaviors, we assign the green zone as the control group and the red zone as the treated group. Our hypothesis is that, in the absence of COVID-19 and associated public policies, the dropout trends between both zones would have been similar on average. This institutional framework includes both direct and indirect factors that could influence students' decisions to drop out. First, there is a direct effect of the pandemic, as students residing in a red zone are subject to the direct impacts of higher numbers of (recorded) cases. Second, there is the potential indirect effect of the implementation of stricter lockdown policies in response to increased numbers of cases, which is of particular interest to us here. Through an examination of this quasi-natural experimental situation, we can refine our previous analysis by providing causal evidence of the impact of different levels of policy stringency on student dropout.

Formally, using a difference-in-differences approach, we estimate the following equation:

$$y_{ij} = \alpha + \beta \text{COVID}_i + \delta \text{Red}_i + \rho \text{COVID}_i \times \text{Red}_i + \mathbf{X}_i' \delta + \Theta_j + \epsilon_i \quad (2)$$

The coefficient of interest, ρ, measures the difference between the red and green conditions for individuals in the COVID-19 cohort. The dependent variable is a binary variable, equal to 1 if the individual is observed in the set of individuals enrolled for the subsequent academic year. We introduce the dummy variable, Red_i,a dummy variable indicating whether the urban area of individual i belongs to the red zone, which thus takes a value of 1 if the observation is in the treated group. $\mathbf{X}_i'$ represents a vector of individual controls, Θ_j represents university fixed effects and ϵ_i is the error term clustered at the university level.

The validity of our estimation strategy relies on the parallel trend assumption, i.e. the assumption that there is no difference in trends in dropout between the two areas outside the treatment period. We provide evidence supporting this assumption in Figure 5.

5 COVID-19 and University Enrollment

5.1 The Impact of COVID-19 on Student Drop-out

Figure 3 presents the overall trends for our three key variables: enrollment, exam attendance, and degree attainment. The figure shows that each year, approximately 70% of the total population tends to re-enroll for the following year, approximately 90%, and around 70% of those in what would normally be the final year of their program successfully obtain their degree.[7]

Figure 3 presents a detailed analysis of changes in educational outcomes during the pandemic. Students observed during the 2020-21 academic year had a 3 percentage point lower likelihood of re-enrollment compared to the previous year (two-tailed t-test, t = 62.876, $p < 0.000$). In other words, the decrease observed in the first academic year following the start of the pandemic is roughly equivalent in size to the cumulative decline in re-enrollment over the preceding 10-year period. Interestingly, however, we find only a 0.1% decrease in the probability of exam attendance (two-tailed t-test, $t = 3.55$, $p < 0.001$), and a 2 percentage point decrease in graduation rate (two-tailed t-test, $t = 23.531$, $p < 0.000$). These two last findings may be attributed to the notions that online exams increased exam attendance and that universities implemented less demanding exams given the significant disruptions students faced in their university education .

Table 2 presents a formalization of the initial findings derived by estimating Equation 1 for different subgroups. Column (1) of panel A provides an estimate using the overall sample, and the following columns provide estimates first by area of study and then by level of degree program (i.e. undergraduate, master's, PhD). The columns in panel B give estimates derived from separate analyses for each year level in the Bologna system to account for the potential influence of the expected time lapse between completing a year of study and entering the labor force. This factor can significantly impact an individual's ability to dedicate themselves to their studies, particularly during a pandemic.

Panel A in Table 2 reveals that overall, students' probability of re-enrollment for the

[7]Note that in the dataset, the variable obtaining a degree is coded as missing if the academic year is not a graduating year.

2020-2021 academic year dropped by 10.6% compared to the previous academic year, controlling for basic demographic characteristics X_{it} in Equation 1. Further disaggregation of the analysis by area of study indicates that students in all areas were more likely to drop out, with a decrease in the probability of re-enrollment of about 10% for students in non-STEM programs, 9.7% for those in the life sciences, and 11% for those in hard-STEM. Columns (5) to (7) show that it was undergraduate students specifically who were more likely to drop out the pandemic (by 16.7%).

Panel B of Table 2 reveals significant heterogeneity with movement through degree programs, as the estimated coefficient varies for almost every individual year considered independently. Students in their first, second and third year after entering university were the most likely to drop out ($\beta = 0.791$, $\beta = 0.827$ and $\beta = 0.914$, respectively). The third year is the expected graduation year for undergraduates under the current (post-Bologna) university system in France, after which students may be expected to directly transition into the labor force. But first- and second-year undergraduate students, who have recently entered university, may have been discouraged by the pandemic, decreasing their motivation to continue their studies. Students who were in a good position to enter the labour market were also less likely to re-enroll – the probability decreased by 7.2% in the pandemic among those who had been enrolled in a fifth year (the graduation year for a master's degree).

5.2 Alternative Measures of Enrollment

Table 3 replicates panel A of Table 2 for alternative measures of dropout: probability of graduation (for students in a graduation year) and attendance at one or more final exams. The inclusion of these measures serves two purposes. First, it addresses the measurement error resulting from teachers implementing less difficult exams in the year of the COVID-19 pandemic, which increases the likelihood of students being observed for the following year. This inherent bias would tend to decrease the estimated impact of the pandemic on re-enrollment, as making students more likely to pass their exams would also make them more likely to enroll for the following academic year. Furthermore, extensive evidence demonstrates the existence of a grading bias during the pandemic (Chan, 2022), which logically translates into a higher likelihood of graduation. Second, it considers pre-existing characteristics associated with dropout that go beyond academic performance alone. For example, non-attendance at final exams may serve as an initial step towards university dropout, which our previous measures may not fully capture. Moreover, such behavior is expected to have been more pronounced during the pandemic, given the increased rates of student absenteeism and lack of motivation to study already extensively highlighted by practitioners and researchers (Chen et al., 2022).

Panel A of Table 3 presents the overall impact of the pandemic on students' likelihood of graduating. Interestingly, the results indicate that, on average, the cohort that was first exposed to the pandemic was 8.2% less likely to graduate than the previous cohort. This finding may be seen as somewhat surprising, as many university instructors adjusted the difficulty of their exams to accommodate the extraordinary circumstances of the pandemic (Chan, 2022), which in principle should increase students' likelihood of graduating. The results by area of study reveal noteworthy variations. Specifically, degree completion rates were lowest among students enrolled in in hard-STEM programs ($\beta = 0.849$), followed by non-STEM students ($\beta = 0.909$). No decrease in graduation rate is observed for students in the life sciences. The lack of an increase in dropout rate in these disciplines might be due to students in medical faculties, whose rigorous admissions selection process may result in a cohort of students who are less likely to drop out. Furthermore, we found that undergraduate students overall were 14.9% less likely to obtain their degrees in the pandemic year, while we did not observe a significant impact of the pandemic on graduate students' likelihood of graduating. This difference could potentially be attributed to the fact an expectation among final-year graduate students of being able to enter the labor force upon graduation, stimulating them to make the effort to graduate in time.

Panel B of Table 3 reveals a contrasting finding: a lack of significant change in attendance at final exams in the pandemic year compared to the previous year—apart from increases in attendance at exams in the non-STEM, undergraduate and graduate subsamples (of 11.3%, 16.8% and 14.8% respectively). These results can be explained by the definition of our main variable, which defines final exam attendance as showing up for at least one exam. Since the majority of exams were conducted online, students were unlikely to completely miss all of them. However, not all areas of study and degree levels examined in panel B exhibit significant effects.

5.3 Heterogeneity of the Impact of COVID-19 on Student Dropout

Here, we expand on our previous analysis by investigating heterogeneity in dropout behaviors during the pandemic based on individual characteristics. Specifically, we consider four key characteristics: gender, socioeconomic status, nationality (French or foreign), and free lunch status. We estimate the following specification to quantify the marginal effect of these specific characteristics relative to the previous years.

$$y_{ijt} = \alpha + \sum_{\substack{t=2013 \\ t\neq 2019}}^{2020} \beta_t \text{year}_t + \delta X_i + \sum_{\substack{t=2013 \\ t\neq 2019}}^{2020} \gamma_t \text{year}_t \times X_i + \mathbf{X}_i' + \Theta_j + \epsilon_{it} \tag{3}$$

The parameter of interest, γ_t, represents the coefficient for the characteristics X of individual i in year t. We can test for pre-trends in a manner similar to an event study design by estimating the relative difference between 2020 and the previous years for each set of individual characteristics. Specifically, each demographic is compared to a reference group (e.g. comparing women to men), with the resulting coefficient interpreted as the first difference for each characteristic. On this basis, it can be argued, in the absence of pre-trends, that the COVID-19 pandemic led to differential dropout behaviors depending on individual characteristics. We present the estimates of Equation 3 in Figure 4. The figure is divided into six panels, each representing a different demographic group. The top panel presents results for three demographic characteristics: gender, nationality, and free lunch status. The bottom panel shows the heterogeneity analysis for three different socioeconomic status groups, with low SES as reference. The coefficients are expressed relative to a reference academic year, 2018-2019, and the red line indicates an odds ratio of 1.

Figure 4 presents two significant sources of heterogeneity that exhibit statistical differences from their pre-trends. Specifically, our findings indicate that women were more likely to re-enroll compared to the previous year, while middle-low SES students were more likely to re-enroll than low-SES students. The higher likelihood of re-enrollment among women might be attributable to stronger study habits or a greater ability to make intertemporal tradeoffs, which enabled them to stay on track during the pandemic. On the other hand, differential re-enrollment rates between middle-low and low SES students may be explained by differences in living conditions, or by a lack of availability of digital devices in low-SES households to study during the pandemic. However, these estimates do not support the hypothesis of an association between either higher SES or free lunch status and dropout behaviors.

We also replicate this analysis with our alternative measures of enrollment, likelihood of graduating and attendance at final exams. The results are presented in Appendix B.1. Figure B1 presents the heterogeneity analysis on the likelihood of graduating. We observe a slightly lower likelihood of middle-high and high-SES students obtaining their degree compared to low-SES students. This finding might potentially be explained by possible over-grading of pupils from underprivileged backgrounds. On the other hand, we do not find compelling evidence that other demographics are associated with the graduation rate. Figure B2, on the other hand, shows significant heterogeneity in the likelihood of attending at least one exam. Specifically, we find that male students, non-french students, students with free lunch status, and low-SES students compared to Middle-Low SES were significantly less likely to attend at least one final exam.

5.4 Policy Stringency and University Dropout

In Section 5.1, we compare different years to assess the impact of COVID-19 on university dropout. But this approach lacks precision in analyzing the effect of lockdown policies on academic dropout. To address this limitation, we employ a natural experiment that occurred in France at the end of the first lockdown, as described in Section 4.2. This institutional setting provides the opportunity to evaluate the extent to which the severity of the pandemic and the stringency of the resulting policies impacted students' enrollment behaviors. We begin by conducting a pre-trends analysis to confirm that the red and green zones exhibited similar dropout dynamics before the pandemic. We also compare student characteristics between the two zones to ensure a balanced treatment based on these attributes (see Appendix B.3). Finally, we present our primary analysis and conduct robustness checks to validate the findings.

Figure 5 presents dropout and graduation probabilities from the academic year 2012-2013 to 2019-2020. The trends in differential dropout rates in the two zones prior to the pandemic exhibit are similar, with no noticeable differences observed. Table 4 presents the difference-in-difference estimates which we use to evaluate the extent to which the stringency of disease lockdown policies impacted dropout and changed graduation rate. We therefore report the estimates derived by using Equation 2 on data from different timespans. We first constitute a control group consisting of all available student-years (i.e. from 2013 to 2019 inclusive), and then use just the academic year 2019-2020, the cohort most likely to be close to the next, pandemic year, as the control. We then extend the timespan of the control group by one year in Column (3), ant then by two and three years in Column (4) and (5), respectively.

Our estimates do not reveal any significant effect of policy stringency on dropout behaviors (failure to re-enroll, non-attendance at exams) or graduation rate. However, we do observe a small decline in the likelihood of graduating when the previous academic year is used as the control. This effect might be driven by the spike in the graduation rate that occurred in the year preceding the COVID-19 pandemic (see Fig. 5b). With control groups including more than one pre-pandemic year, we do not find evidence of an effect of policy stringency on graduation.

We then conduct several sensitivity checks to assess the robustness of our findings. Initially, we examine an alternative measure of the treatment variable, where the reference group is constituted by taking the average dropout rate for all the available years before the COVID-19 pandemic. Furthermore, we investigate the results by separating the Ile-de-France region, including Paris and the surrounding area, from the rest of the red zone (Appendix D.1). This differentiation is due to the unique characteristics of the Ile-de-France region, where universities are highly concentrated and differ significantly both in terms of their selectivity and in the contents' of their degree from those in the rest of the country. Finally, in Appendix D.2, we conduct a placebo analysis that leads to a similar conclusion, with no evidence that policy stringency affected university dropout and graduation rates.

5.5 Potential Mechanisms

Here we examine two potential factors that may have influenced individual decisions to withdraw from university: the labor market conditions at the end of the 2019-2020 academic year, and the severity of the local pandemic situation in 2020. As highlighted by the seminal work of Becker (1964), the decision to pursue an additional year of study involves weighing the potential returns against the associated opportunity costs. The COVID-19 pandemic significantly reduced labor market opportunities for students. According to this theoretical framework, these unfavorable economic conditions should make students more likely to extend their enrollment in university for an additional year. Conversely, more severe local pandemic conditions may be expected to impose a greater mental burden on students (e.g. Guse et al., 2021), which could decrease their likelihood of enrolling for the following academic year.

To assess the potential impact of these mechanisms, we use administrative datasets that offer detailed geographical and temporal granularity (see Appendix A). We measure labor market opportunities using quarterly unemployment rates at the finest geographical unit of analysis for which unemployment rate data are available in France, the "employment zone" - "*Zone d'emploi*" - (or "labour market area") level.[8] We begin by calculating the quarterly unemployment rate during the period in each year from 2016 to 2020 when students decided whether to re-enroll for the upcoming academic year. We then determine the difference between these specific quarterly rates and the structural level of unemployment, measured as the average over the years 2016–2019. We take a similar approach to calculate local exposure to the pandemic, using excess mortality.[9] These calculations are based on a dataset of individual death records from January 1, 2018, to December 31, 2020 from the "*Fichier des Décès Quotidiens*" (daily record of deaths).[10] The indices for calculating unemployment rates and local pandemic severity are presented in Equations 4 and 5, respectively. This approach has the advantage of quantifying the relative difference between the value of the variables of interest in the COVID-19 year and their structural level as measured in the previous year.

[8]An employment zone (or labor market area) is a geographic unit whose boundaries are chosen to delimit an area that includes both the workplace and the residence of the majority of a local labor force. INSEE divides France into 306 employment areas, which are used to study local labor markets. https://www.insee.fr/fr/metadonnees/source/indicateur/p1660/description

[9]At the beginning of the pandemic, testing capacities and strategies varied considerably by region and time (Kung et al., 2021; Rivera, Rosenbaum, and Quispe, 2020; Balmford et al., 2020; Silverman, Hupert, and Washburne, 2020; Yorifuji, Matsumoto, and Takao, 2021), even in France. We thus follow Brandily et al. (2021)'s in measuring local exposure to the pandemic through excess mortality, which provides a metric of the local severity of the pandemic that is not biased by those variations.

[10]Individual death records are available at the municipal level. We then aggregate this municipality information at the employment area level in order to match the territorial division used for unemployment rates.

$$UR_{ze} = \frac{UR_{ze}^{2020} - [0.2 \times \sum_{i=2016}^{n=2020} UR_{ze}]}{UR_{ze}^{2016}} \tag{4}$$

$$D_{ze} = \frac{N_{ze}^{2020} - [0.5 \times (N_{ze}^{2018} + N_{ze}^{2019})]}{Population_{ze}^{2014}} \tag{5}$$

UR_{ze} can be interpreted as the change in the unemployment rate compared to the structural unemployment rate as measured for the corresponding year in a given employment zone ze. Positive values reflect a decrease in employment during the pandemic, which occurred in many employment zones due to various French government policies aimed at mitigating the impact of the pandemic on the labor market. D_{ze} can be interpreted as excess mortality due to the COVID-19 pandemic, in comparison to its structural level, defined as mortality (rate of deaths in the population) in 2014. Figure 6 presents the geographical distribution of excess unemployment and excess mortality.

The left panel of Figure 6 shows a lighter color in eastern France, indicating a greater increase in mortality during the first year of the pandemic in this region. This finding is consistent with the results of Brandily et al. (2021). It may be explained in part by the greater spread of the disease in this area during the early stages of the pandemic, leading to increased mortality. But the right panel of Figure 6 does not show any clear geographical concentration of excess unemployment. Our findings reveal that unemployment rates were higher in regions with stricter policies (two-sided t-test, $p < 0.001$), as was excess mortality (two-sided t-test, $p < 0.001$). Appendix E provides a more comprehensive analysis of the relationship between the two potential mechanisms. The absence of a geographical relationship between unemployment and pandemic intensity is particularly significant, as it allows us to distinguish between their impacts on students' enrollment decisions.

Figure 7 illustrates the relationship between the unemployment rate, excess mortality, and enrollment and graduation rates at the employment zone level. Our approach to calculating enrollment outcomes is similar to the approach we take to calculate excess unemployment and mortality. In other words, we compute the standardized difference in enrollment behaviors between the COVID-19 cohort and previous years, expressed as a rate relative to enrollment behaviors in 2012, the first year available for analysis. This approach has the advantage of quantifying the extent to which the COVID-19 cohort altered its enrollment behaviors at a fine-grained geographical level, while taking into account inherent structural variations in students' behaviors. Our dataset specifies three locations for each student at the employment zone level: their university, their residence, and their parents' residence. We focus specifically on the employment zone associated with the municipality of the university, assuming that students are likely to seek employment opportunities near their educational institution. Figure 7a presents the relationship between re-enrollment and these plausible mechanisms, while Figure 7b replicates that analysis for the graduation rate.

Figure 7a does not provide compelling evidence that either unemployment or mortality determined enrollment behavior, either in terms of effect size or explanatory power. These findings suggest that neither recent variation in local employment opportunities nor the local severity of the pandemic played a role in determining university students' decisions on whether or not to re-enroll. Figure 7b shows a relationship between the local unemployment rate and students' likelihood of graduating. An increase of one point in excess unemployment is associated with an 0.9-point increase in the likelihood of graduating. However, no evidence was found of a relationship between intensity of exposure to COVID-19, as measured by local excess mortality and the likelihood of graduating. Appendix C presents similar analyses for both of the other locations characterizing the students: their place of residence and that of their parents, with similar results.[11] No conclusive evidence was found of any impact of these mechanisms on the probability of being present for at least one exam.

6 Conclusion

Drawing on a comprehensive dataset encompassing all university students in France since 2012, this paper provides evidence that students' likelihood of dropping out increase during the pandemic. Specifically, the initial findings reveal a 10.6% decrease in the chances of re-enrollment for the COVID-19 cohort compared to the previous year's cohort. This is equivalent to the cumulative decline observed in French higher education institutions over the preceding decade. This decline cannot be attributed to changes in grading practices or attendance at final exams, indicating a genuine decrease in re-enrollment rates. The impact is predominantly observed among male students and those of non-French nationality. These findings suggest that pandemic-induced dropouts may have adverse effects on employment opportunities for these groups of students.

We began by examining the overall effect of the pandemic on students' enrollment behaviors. We then refined the analysis by leveraging a natural experiment in France, where policies of differing stringency were implemented in different areas to contain the spread of the virus during the first wave of the pandemic in France. This setting provided the opportunity to analyze whether and how the intensity of lockdown policies influenced students' educational outcomes. Leveraging this quasi-natural experiment to test for such effects we did not find evidence that stringent policies caused (or prevented) dropout. Our null result on the marginal impact of the differential extension of lockdown in France can

[11] The equivalent results of these different analyses can be understood in terms of two main explanations: i) students' location is similar across measures, and ii) the (lack of) effect is consistent across measures. Our findings are compatible with the first, as 87.9% of students live in the employment zone where their university is located.

be at least partially explained by the hypothesis that the first, universal lockdown was in itself enough to cause students to leave university. We then conducted our analysis at a detailed geographical level, examining whether local labor market opportunities or the local severity of the pandemic itself induced significant changes in enrollment behaviors. We did not find evidence supporting the idea that re-enrollment was influenced by either factor. This suggests that students' decisions in times of crisis are more likely to be driven by individuals' perceptions of the situation than by their demographics.

The findings of this study carry important policy implications for educational institutions and policymakers. First, the observed decrease in university re-enrollment rates in the COVID-19 cohort highlights the need for targeted support and interventions for students facing challenges during pandemics. Counseling services, financial assistance programs, and mental health support could help mitigate the negative impact of such external shocks on students' educational trajectories. Second, the lack of significant effects of lockdown stringency on enrollment behaviors calls for nuanced policy responses, balancing disease lockdown measures with educational continuity. Additionally, policies targeting first- and third-year undergraduate students, who were the most affected by the pandemic, could focus on personalized support and guidance during these critical stages of their academic journey. Finally, given the exacerbation of inequalities among university students during the pandemic, policymakers should prioritize measures that address structural barriers, support underprivileged students, and promote equal access to quality education. Incorporating these policy implications into strategic planning may help policymakers effectively respond to the challenges brought about by pandemics and work towards a more resilient and inclusive higher education system.

The study has identified several potential areas for future research, in light of its limitations. First, conducting cross-country comparative analyses could reveal common patterns and variations in enrollment decisions and dropout rates across different educational systems. Second, examining the long-term labor market effects of the pandemic on students' career trajectories and economic prospects should provide insights into potential disparities in labor market outcomes. Third, exploring the role of mental health and well-being in enrollment behaviors and academic performance during the pandemic could offer insight into valuable support measures for students. Finally, delving into the influence of demographic factors on university dropout should deepen our understanding of how external shocks interact with individual characteristics, and contribute to existing knowledge on inequalities in higher education. Together, these further studies should enrich our understanding of the multifaceted impact of the COVID-19 pandemic on higher education and its implications for students' futures.

Overall, our findings suggest that the COVID-19 pandemic has had a significant impact on university student dropout rates in France, varying across demographic characteristics, fields of study, and institutional contexts. Understanding these impacts is crucial for addressing the challenges facing students and mitigating the exacerbation of inequalities in higher education. Further research and policy efforts are needed to support students and promote equitable access to education during and beyond the pandemic.

Acknowledgements

This paper benefited from discussions and helpful comments from Julien Grenet, Marion Leturcq, Camille Terrier and seminar/conference participants at 8th LEER (Leuven), TEPP 2023 (Poitiers), UCL and Ined. We acknowledge financial support from the Region Île-de-France under grant number EX061002 - 21010352 (chaire en sciences humaines et sociales). Data access through the Centre d'accès sécurisé aux données (CASD) has been supported by this grant. We are also grateful to Christopher Leichtnam and Paul Reeve for their help in editing the manuscript for grammar and syntax.

Declarations of interest

Declarations of interest: none.

Statement

Statement: During the preparation of this work the authors used ChatGPT in order to improve the clarity of the writting. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

References

Aalto, A.-M., D. Müller, and J. L. Tilley (2022). "From Epidemic to Pandemic: Effects of the COVID-19 Outbreak on High School Program Choices in Sweden". In: *Latest version: IZA Discussion Paper* 15107.

Adamopoulou, E. and G. M. Tanzi (2017). "Academic drop-out and the great recession". In: *Journal of Human Capital* 11.1, pp. 35–71.

Agostinelli, F. et al. (2022). "When the great equalizer shuts down: Schools, peers, and parents in pandemic times". In: *Journal of public economics* 206, p. 104574.

Aina, C. et al. (2018). "The economics of university dropouts and delayed graduation: a survey". In: *IZA Discussion Papers* 11421.

Andrew, A. et al. (2020). "Inequalities in children's experiences of home learning during the COVID-19 lockdown in England". In: *Fiscal studies* 41.3, pp. 653–683.

Atkinson, A. B. and S. Morelli (2011). "Economic crises and inequality". In: *UNDP-HDRO occasional papers* 2011/6.

Aucejo, E. M. et al. (2020). "The impact of COVID-19 on student experiences and expectations: Evidence from a survey". In: *Journal of public economics* 191, p. 104271.

Balmford, B. et al. (2020). "Cross-country comparisons of COVID-19: Policy, politics and the price of life". In: *Environmental and Resource Economics* 76.4, pp. 525–551.

Becker, G. S. (1964). *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education.* University of Chicago press.

Betthäuser, B. A., A. M. Bach-Mortensen, and P. Engzell (2023). "A systematic review and meta-analysis of the evidence on learning during the COVID-19 pandemic". In: *Nature Human Behaviour*, pp. 1–11.

Blom, E., B. C. Cadena, and B. J. Keys (2021). "Investment over the business cycle: Insights from college major choice". In: *Journal of Labor Economics* 39.4, pp. 1043–1082.

Bonneau, C., P. Charrousset, et al. (2021). "Quelle démocratisation des grandes écoles depuis le milieu des années 2000?" In: *Institut des politiques publiques (IPP).*

Bonneau, C. and S. Grobon (2022). "Unequal access to higher education based on parental income: evidence from France". In: *Documents de travail du Centre d'Économie de la Sorbonne.*

Brandily, P. et al. (2021). "A poorly understood disease? The impact of COVID-19 on the income gradient in mortality over the course of the pandemic". In: *European economic review* 140, p. 103923.

Bulman, G. and R. Fairlie (2022). "The Impact of COVID-19 on Community College Enrollment and Student Success: Evidence from California Administrative Data". In: *Education Finance and Policy*, pp. 1–20.

Bulman, G., R. Fairlie, et al. (2021). "Parental resources and college attendance: Evidence from lottery wins". In: *American Economic Review* 111.4, pp. 1201–1240.

Chan, C. K. Y. (2022). "A review of the changes in higher education assessment and grading policy during covid-19". In: *Assessment & Evaluation in Higher Education*, pp. 1–14.

Charousset, P. and M. Monnet (2022). "Gendered Teacher Feedback, Students' Math Performance and Enrollment Outcomes: A Text Mining Approach". In: *PSE Working Paper* 19.

Chen, D. L. et al. (2022). "Grit and academic resilience during the COVID-19 pandemic". In: *INSEAD Working Paper* 02.

Dang, T. H. et al. (2022). "Do positive income shocks benefit children's education? Evidence from Vietnam". In: *Applied Economics*, pp. 1–25.

Dincher, M. and V. Wagner (2021). "Teaching in times of COVID-19: determinants of teachers' educational technology use". In: *Education Economics* 29.5, pp. 461–470.

Ferreira, F. H. and N. Schady (2009). "Aggregate economic shocks, child schooling, and child health". In: *The World Bank Research Observer* 24.2, pp. 147–181.

Grewenig, E. et al. (2021). "COVID-19 and educational inequality: How school closures affect low-and high-achieving students". In: *European economic review* 140, p. 103920.

Gury, N. (2011). "Dropping out of higher education in France: a micro-economic approach using survival analysis". In: *Education Economics* 19.1, pp. 51–64.

Guse, J. et al. (2021). "Mental burden and perception of the study situation among undergraduate students during the COVID-19 pandemic: a cross-sectional study and comparison of dental and medical students". In: *BMJ Open* 11.12.

Kung, S. et al. (2021). "Underestimation of COVID-19 mortality during the pandemic". In: *ERJ open research* 7.1.

Montmarquette, C., S. Mahseredjian, and R. Houle (2001). "The determinants of university dropouts: a bivariate probability model with sample selection". In: *Economics of education review* 20.5, pp. 475–484.

Moulin, L., D. Flacher, and H. Harari-Kermadec (2016). "Tuition fees and social segregation: lessons from a natural experiment at the University of Paris 9-Dauphine". In: *Applied Economics* 48.40, pp. 3861–3876.

Parolin, Z. and E. K. Lee (2021). "Large socio-economic, geographic and demographic disparities exist in exposure to school closures". In: *Nature human behaviour* 5.4, pp. 522–528.

Rivera, R., J. E. Rosenbaum, and W. Quispe (2020). "Excess mortality in the United States during the first three months of the COVID-19 pandemic". In: *Epidemiology & Infection* 148.

Schanzenbach, D. W. and S. Turner (2022). "Limited supply and lagging enrollment: Production technologies and enrollment changes at community colleges during the pandemic". In: *Journal of Public Economics* 212, p. 104703.

Schueler, B. E. and L. C. Miller (2023). "Post-Pandemic Onset Public School Enrollment and Mobility: Evidence From Virginia". In: *Educational Evaluation and Policy Analysis*, p. 01623737231178299.

Silverman, J. D., N. Hupert, and A. D. Washburne (2020). "Using influenza surveillance networks to estimate state-specific prevalence of SARS-CoV-2 in the United States". In: *Science translational medicine* 12.554, eabc1126.

Stantcheva, S. (2022). *Inequalities in the Times of a Pandemic*. Tech. rep. National Bureau of Economic Research.

Svaleryd, H. and J. Vlachos (2022). "COVID-19 and School Closures". In: *Handbook of Labor, Human Resources and Population Economics*, pp. 1–25.

Tuition Fees in France (2022). Campus France. https://www.campusfrance.org/en/tuition-fees-France.

Wachter, T. V. (2020). "The persistent effects of initial labor market conditions for young adults and their sources". In: *Journal of Economic Perspectives* 34.4, pp. 168–194.

Werner, K. and L. Woessmann (2021). "The legacy of covid-19 in education". In.

Yorifuji, T., N. Matsumoto, and S. Takao (2021). "Excess all-cause mortality during the COVID-19 outbreak in Japan". In: *Journal of epidemiology* 31.1, pp. 90–92.

Figures and Tables

Figure 1: Timeline of the Policy Response to the COVID-19 Pandemic

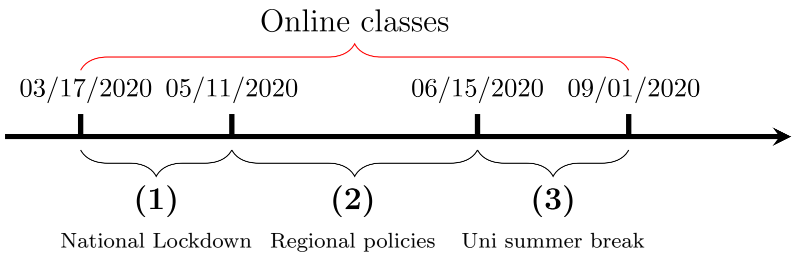


Figure 2: Regional Lockdown Policies

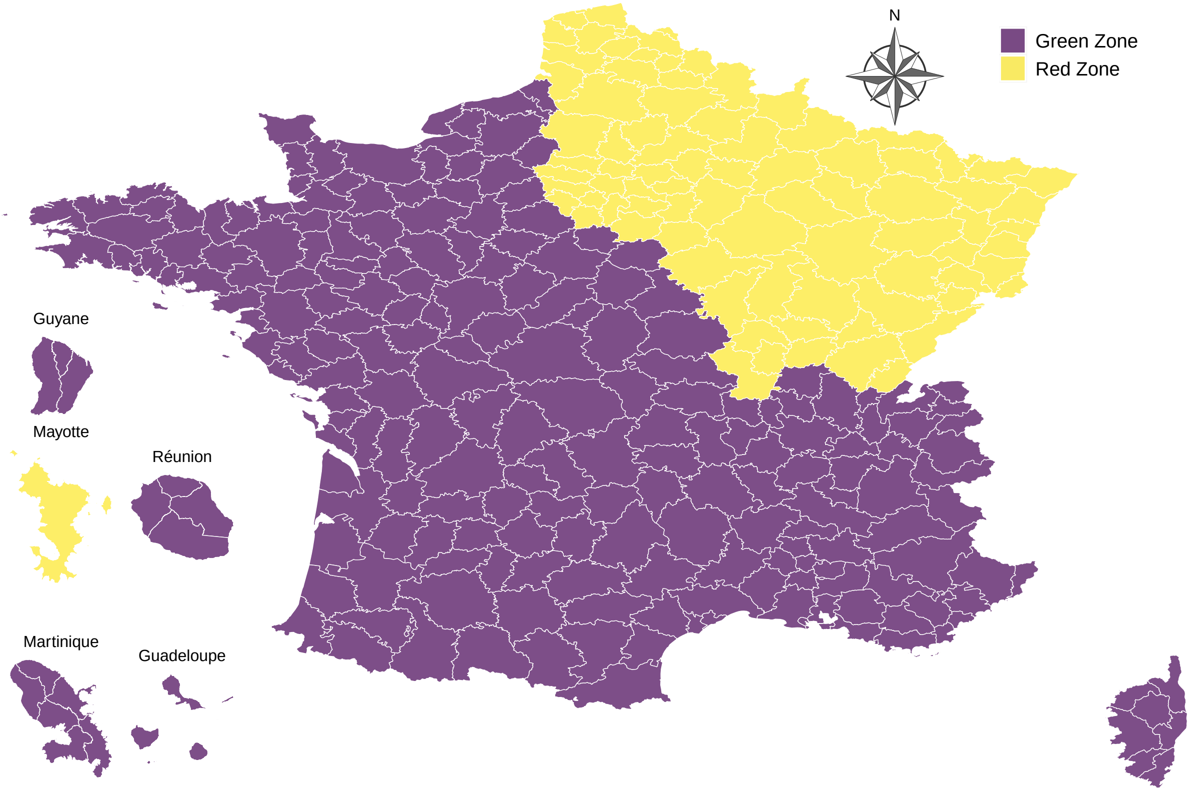
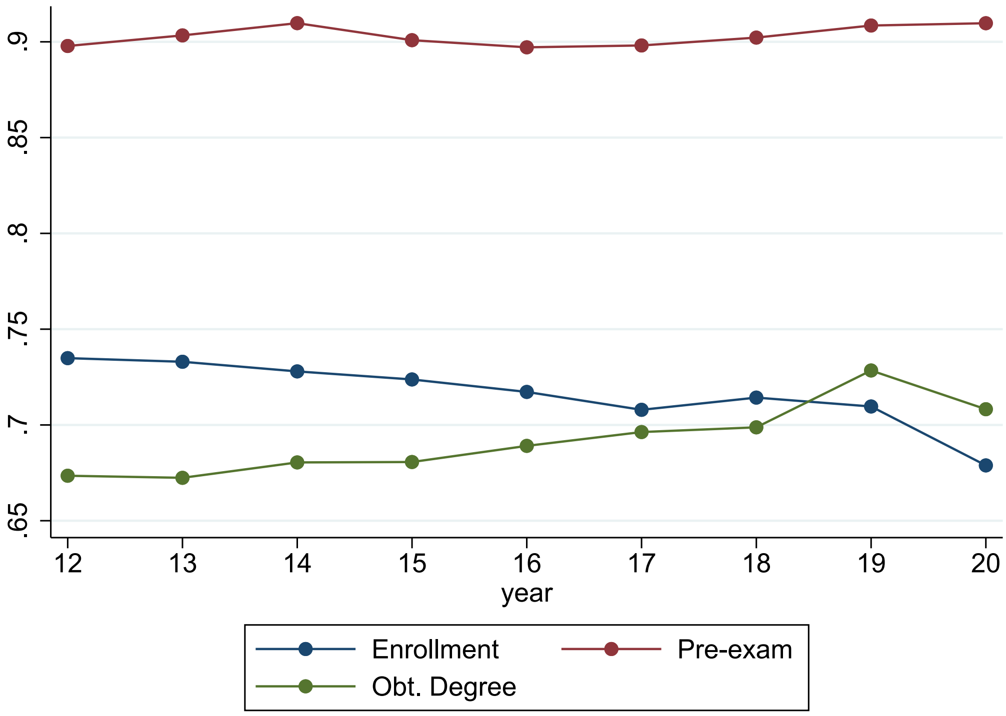
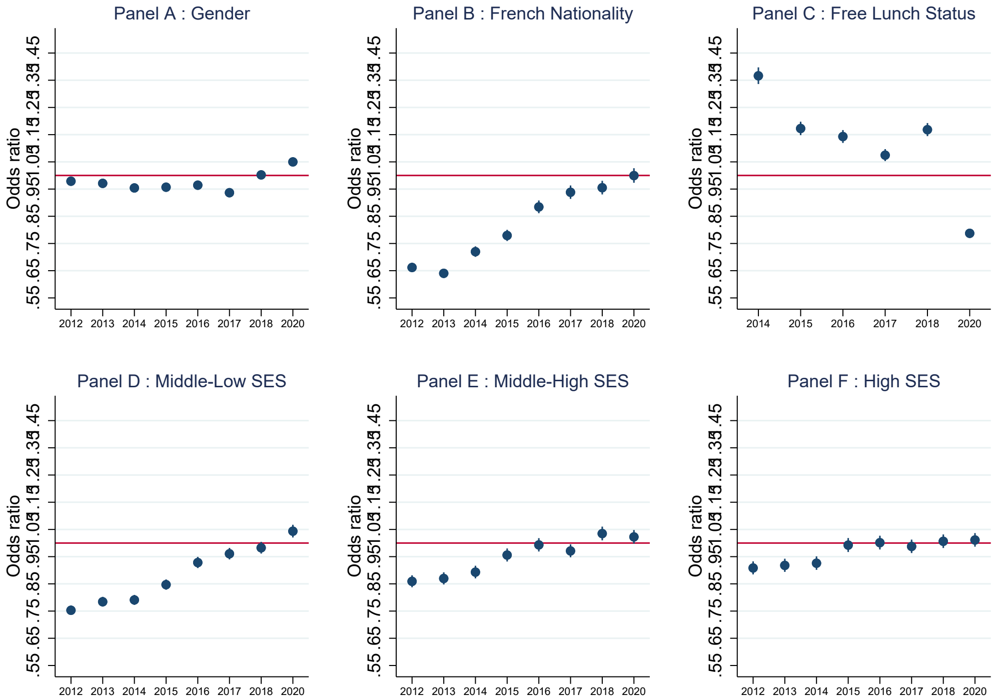


Figure 3: Enrollment Behaviors between 2012 and 2020



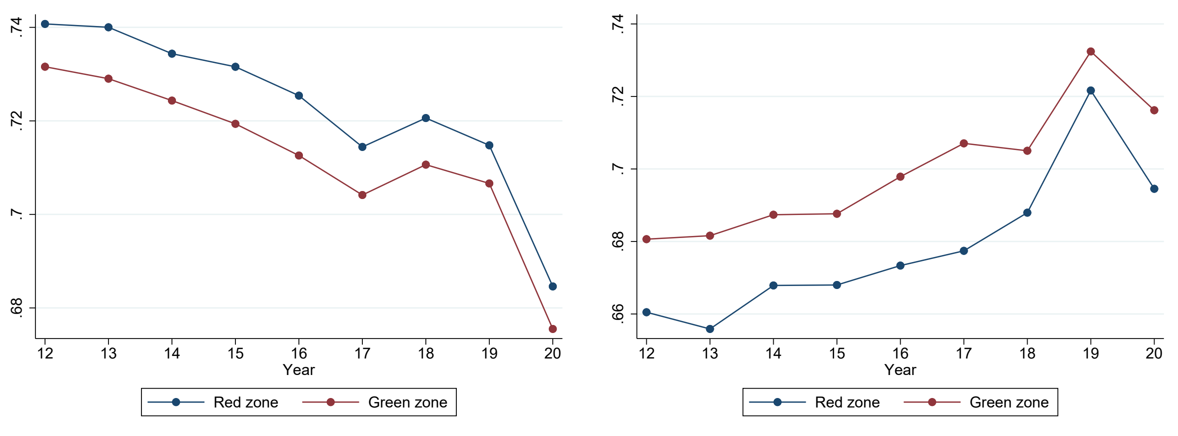
Notes: The figure presents the yearly averages of our educational outcomes. Each dot represents the average value of the respective outcome for the corresponding calendar year. "*Enrollment*" is defined as 1 when an individual is observed in the subsequent academic year. The variable "*Pre-exam*" takes a value of 1 if the individual attends at least one final exam, while "*Obt. degree*" indicates whether the individual successfully obtained their degree at the end of a graduating academic year.

Figure 4: Demographics and Likelihood to Drop-out



Notes: The figure presents the heterogeneity analysis based on a logit model (Equation 3). We cluster standard errors at the university level. The dependent variable in focus is the probability of re-enrollment for the ensuing academic year. The coefficient shown in the graph represents the odds ratio for the interaction term between the demographic category and the year. The reference year is the one preceding the pandemic. An odds ratio that overlaps with the red horizontal line indicates a significant change in the likelihood of dropping out for members of the corresponding demographic during the pandemic. We compute the equation once and plot the relevant parameter for each group on a separate panel to enhance readability.

Figure 5: Pre-trends in Green and Red Zones



(a) Likelihood of Dropping out

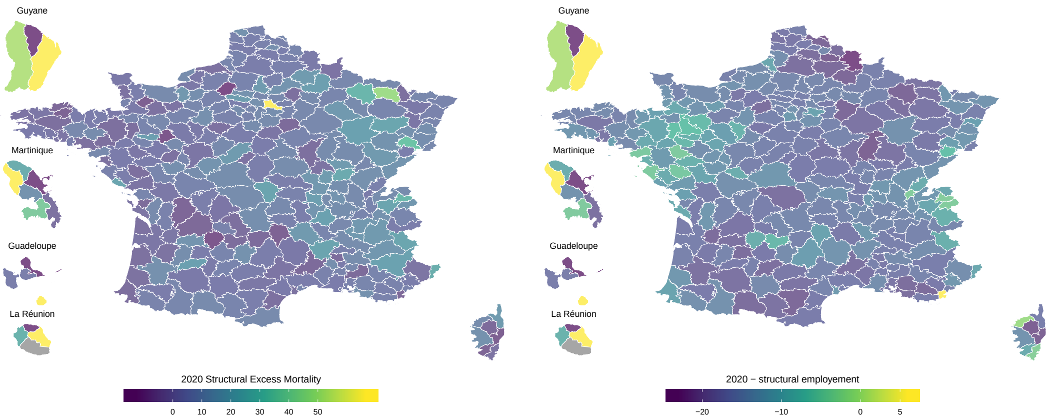
(b) Likelihood of Graduation

Notes: The figure presents the pre-trend analysis for the likelihood of dropping out and graduating for each zone impacted by the natural experiment in France. The measures are for re-enrollment behaviors and graduation rate at the individual level. Each dot represents the average of all areas within each zone for the corresponding year.

Figure 6: Geographical Distribution of Excess Mortality and Unemployment

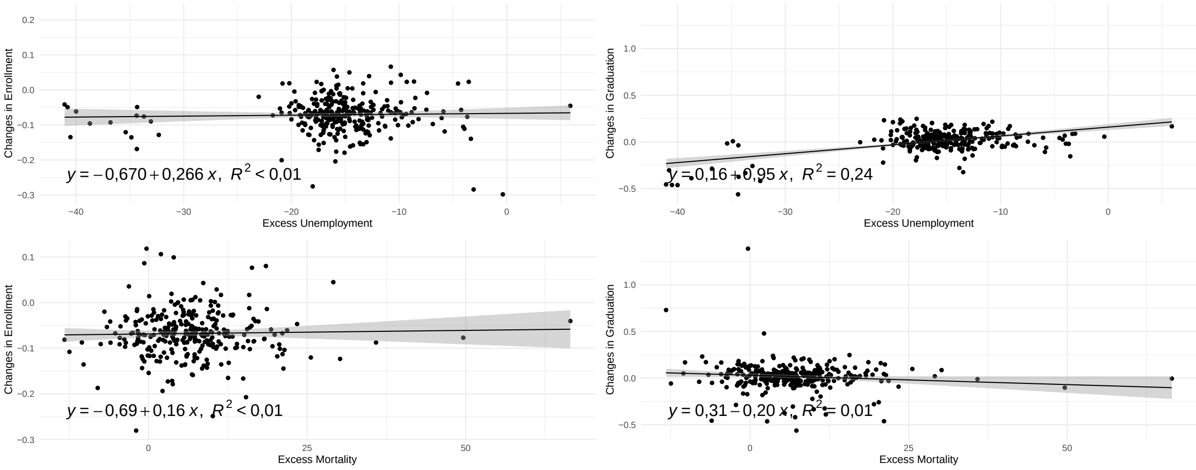
(a) Excess mortality in 2020 during the COVID-19

(b) Changes in unemployement during the COVID-19



Notes: The figure presents the geographical distribution of our two main mechanisms measured at the employment zone level: excess mortality and excess unemployment. The employment zone is the smallest geographical unit for which unemployment rate data is available. There are 306 such zones in France , excluding some DOM-TOM regions such as Mayotte. For both variables, we calculate the difference between the value for the period under scrutiny and the mean for the previous year, and then divide it by the population rate/unemployment rate in the initial period.

Figure 7: Mechanisms behind changes in enrollment and graduation rate at the employment zone level



(a) Re-enrollment rate (b) Graduation Rate

Notes: The figure illustrates the relationship between two potential mechanisms and our two main outcome variables. The left-hand side of the figure shows the likelihood of re-enrollment, while the right-hand side shows the likelihood of graduation. The upper panel on each side depicts the relationship between excess unemployment and the variable of interest, while the bottom panel represents the relationship between excess mortality and the variable of interest. Each dot in the figure represents an observation at the employment zone level, the unit for which we calculate the structural change in enrollment and graduation rates. The line in the figure represents a linear fit based on the equation presented in the corresponding panel.

Table 1: Pre-COVID and COVID Period Cohort Composition

	Treated *COVID-19 cohort*	Baseline *2018-2019*	Difference
Demographics			
Female	0.585	0.588	-0.004***
Low SES	0.245	0.231	0.015***
Middle Low SES	0.218	0.224	-0.006***
Middle High SES	0.198	0.204	-0.006***
High SES	0.339	0.342	-0.003***
French nationality	1.134	1.128	0.006***
Free Lunch Status	0.282	0.220	0.062***

Notes: Each row presents the average value for students enrolled in university in the 2018-2019 and 2019-2020 academic years for the variables listed on the left. Column (1) represents the cohort exposed to COVID-19, and column (2) represents the 2018-2019 cohort. Column (3) gives the results of a two-tailed t-test on the difference in means, with asterisks indicating traditional levels of statistical significance (***, **, * for 0.01, 0.05, 0.1, respectively)..

Table 2: Impact of COVID-19 on Student Dropout

Panel A. Re-enrollment by Area of Study & Degree Level

	Overall	Non-STEM	Soft-STEM	Hard-STEM	UG	G	Ph.D.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2020	0.894***	0.900***	0.903***	0.890***	0.833***	0.990	0.931
	(0.011)	(0.011)	(0.022)	(0.017)	(0.011)	(0.019)	(0.082)
Observations	12,514,873	7,057,280	2,382,261	3,074,658	7,665,823	4,223,539	412,352
Log Likelihood	-7,151,160	-4,161,016	-1,189,992	-1,739,139	-4,192,663	-2,554,916	-235,620.78

Panel B. Re-Enrollment by Year of University Study

	Overall	First year	Second year	Third year	Fourth year	Fifth year	Sixth year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2020	0.894***	0.791***	0.827***	0.914***	1.081	0.928***	0.913**
	(0.011)	(0.014)	(0.015)	(0.025)	(0.052)	(0.026)	(0.034)
Observations	12,514,873	4,021,540	2,164,095	2,180,090	1,593,686	1,561,863	992,576
Log Likelihood	-7,151,160	-2,010,355	-952,702.37	-1,313,474	-654,381.42	-1,000,098	-548,507.97

Notes: This table reports estimates of the probability of re-enrollment for the following year after the academic year 2019-2020 relative to 2018-2019. Year numbering is expressed as the odd-ratio with the 2018-2019 as a reference. The sample includes all students enrolled in a university degree in France from 2012 to 2021. Each column presents a logit regression performed separately on the corresponding sample. The regression includes university fixed effects (to account for differences in university quality) and the student characteristics listed in Table 1. Standard errors (shown in parentheses) are adjusted for clustering at the university level. Asterisks indicate traditional levels of statistical significance (***, **, *, for 0.01, 0.05, 0.1, respectively) The sample is restricted to students enrolled to all university degree in France from 2012 to 2021.

Table 3: Alternative Measures of Drop-out

Panel A. Graduation by Area of Study & Degree Level

	Overall (1)	Non-STEM (2)	Soft-STEM (3)	Hard-STEM (4)	UG (5)	G (6)
2020	0.918***	0.909***	0.902	0.849***	0.851***	1.005
	(0.017)	(0.024)	(0.064)	(0.024)	(0.023)	(0.022)
Observations	3,714,784	2,260,783	534,860	919,060	2,163,500	1,551,206
Log Likelihood	-2,224,720	-1,218,465	-328,213.3	-526,491.42	-1,258,260	-921,975.52

Panel B. Attendance at least at 1 Final Exam by Area of Study & Degree Level

	Overall (1)	Non-STEM (2)	Soft-STEM (3)	Hard-STEM (4)	UG (5)	G (6)
2020	1.055	1.113***	1.027	0.978	1.168**	1.148***
	(0.044)	(0.025)	(0.201)	(0.057)	(0.082)	(0.050)
Observations	10,275,894	6,241,550	1,366,765	2,666,583	1,903,008	1,346,570
Log Likelihood	-3,113,179	-1,906,213	-292,252.58	-858,853.29	-387,487.32	-357,864.7

Notes: This table reports estimates of the relative probability of graduation and exam attendance in 2019-2020 relative to 2018-2019. The sample for panel B consists of all students enrolled in a graduation year in France from 2012 to 2021, while the sample for panel A covers all students enrolled in any degree program at a public university. Each column presents a logit regression performed separately on the corresponding sample. The regression includes university fixed effects (to account for differences in university quality) and the student characteristics listed in Table 1. Standard errors (shown in parentheses) are adjusted for clustering at the university level. Asterisks indicate traditional levels of statistical significance (***,**,*, for 0.01, 0.05, 0.1, respectively).

Table 4: Policy Stringency and University Drop-out

Panel A. Enrollment

	2013 to 2019 (1)	2013 to 2019 (2)	2019 (3)	2018 to 2019 (4)	2017 to 2019 (5)
2020	0.851***	0.856***	0.902***	0.897***	0.901***
	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
Red	1.059**	1.140***	1.132***	1.136***	1.139***
	(0.029)	(0.037)	(0.045)	(0.042)	(0.040)
2020 × Red	0.991	0.999	0.969	0.977	0.981
	(0.025)	(0.020)	(0.019)	(0.017)	(0.016)
Constant	3.386***	3.311***	2.335***	2.433***	2.474***
	(0.123)	(0.096)	(0.070)	(0.071)	(0.070)
Fixed effects	No	Yes	Yes	Yes	Yes
Observations	12,515,064	12,514,873	2,990,348	4,404,934	5,852,941
Log Likelihood	-7,178,223	-7,154,186	-1,776,467	-2,588,150	-3,425,750

Panel B. Graduation

	2013 to 2019 (1)	2013 to 2019 (2)	2019 (3)	2018 to 2019 (4)	2017 to 2019 (5)
2020	1.117***	1.100***	0.948**	1.008	1.030
	(0.031)	(0.027)	(0.022)	(0.019)	(0.021)
Red	0.909*	1.020	1.102***	1.063*	1.046
	(0.045)	(0.026)	(0.038)	(0.036)	(0.034)
2020 × Red	0.987	0.976	0.931**	0.955	0.981
	(0.046)	(0.040)	(0.028)	(0.028)	(0.033)
Constant	2.411***	2.176***	1.832***	2.081***	2.094***
	(0.172)	(0.096)	(0.100)	(0.106)	(0.102)
Fixed effects	No	Yes	Yes	Yes	Yes
Observations	3,715,033	3,714,784	917,855	1,344,205	1,768,524
Log Likelihood	-2,266,725	-2,226,704	-527,857.51	-782,702.03	-1,037,257

Notes: This table reports estimates of the likelihood of re-enrollment for the following year and graduation among students who experienced more stringent COVID-19 policies in the first lockdown extension period (i.e. studying in a red zone) relative to students who experienced less stringent policies (i.e. studying in a green zone). For panel A, the sample covers all students enrolled in a university degree in France between the initial year mentioned for the control sample in each column and 2021. For panel B it consists in all students enrolled in a graduation year in a university degree program in the corresponding years. Each column presents a logit regression performed separately for a given control group time window. The regression includes university fixed effects (to account for differences in university quality) and the student characteristics listed in Table 1. Standard errors (shown in parentheses) are adjusted for clustering at the university level. Asterisks indicate traditional levels of statistical significance (***,**,*, for 0.01,0.05, 0.1, respectively).

Appendix A Variables and Data-sets Used

- Excess unemployment at the employment area level : "*Taux de chômage localisés (par régions, départements et zones d'emploi*"

  INSEE (France's National Institute of Statistics and Economic Studies) estimates unemployment rates in France on a quarterly basis, excluding Mayotte. The numerator in the national rate calculation is the estimated number of unemployed individuals in the country (excluding Mayotte) on a quarterly average basis, obtained from data collected through INSEE's annual CVS (Cadre de vie et Sécurité, or Living environment and safety) survey. The denominator is the total size of the national labor force, including both employed and unemployed individuals. To calculate localized numbers of unemployed individuals by employment area (here, excluding both Mayotte and French Guiana), the number of unemployed individuals used as the numerator in the national rate is distributed proportionally to the monthly number of officially registered jobseekers with no paid employment in each employment area, separately by gender and for three age groups (age 24 or under, ages 25-49, age 50 or over). The resulting data is adjusted for specific seasonal fluctuations in each employment area, as well as the numbers of unemployed individuals in the department or region within which the employment area is situated as measured by the CVS survey. INSEE estimates the number of employed individuals in each area (by place of residence) based on data from three sources: quarterly localized employment estimates, annual estimates of numbers of employed individuals by place of work (drawn from administrative sources as gathered and processed by INSEE's ESTEL system), and census data. It is estimated quarterly and adjusted to match employment figures for the department or region within which the employment area is situated.

  Access from: https://www.insee.fr/fr/statistiques/1893230#consulter.

- Excess mortality: The "*fichier des décès quotidiens*" (daily death records) (daily death records) contain information on all deaths that occurred between January 1st, 2018 and June 5, 2020. Each record includes various details about the death, such as the date, municipality, and type of place of death (e.g., hospital, home, nursing home, etc.). Information about the individual, including their department of residency, gender, and date of birth, is also recorded.

  During the COVID-19 crisis, INSEE increased the frequency of publication of these records. As a result, some compromises were made in terms of quality checks. The records are initially collected by municipalities, and then gradually incorporated into the INSEE datasets as they are provided by the municipalities. It is possible that the records were not complete at the time of our analysis, despite regular updates. For more information and access to these files, please refer to the following URL:

https://www.insee.fr/fr/statistiques/4487854.

- Population density: Large variations in the spatial extent of municipalities and the distribution of population within them can undermine the usefulness and comparability of population density figures calculated based on administrative boundaries. To solve this problem, France's municipal density grid instead divides the territory into 1 km $\times$ 1 km cells and measures population sizes within them, identifying population agglomerations. Municipalities are characterized in terms of the size of these agglomerations, rather than the overall population density within their administrative boundaries. This classification aligns with Eurostat framework, introducing an additional category for very sparsely populated areas, which are more common in France than in other European countries. On the basis of the density grid, municipalities are divided into four categories: high, intermediate, low, and very low density. High and intermediate density municipalities are classified as urban, while low and very low density municipalities are classified as rural. Population data are drawn from INSEE's Fidéli database of housing and individual demographic files. The density grid was updated in 2020 to align it with European methodology. The current method used to produced it is harmonized with the definition of the boundaries of city functional areas (*aires d'attraction des villes*) as defined in the division of the territory based on the 2020 population census (*zonage en aires d'attraction des villes*). The downloadable file provides the composition of the density grid by municipalities as defined on January 1, 2022, along with the distribution of the population at the four density levels.

  https://www.insee.fr/fr/information/2114627

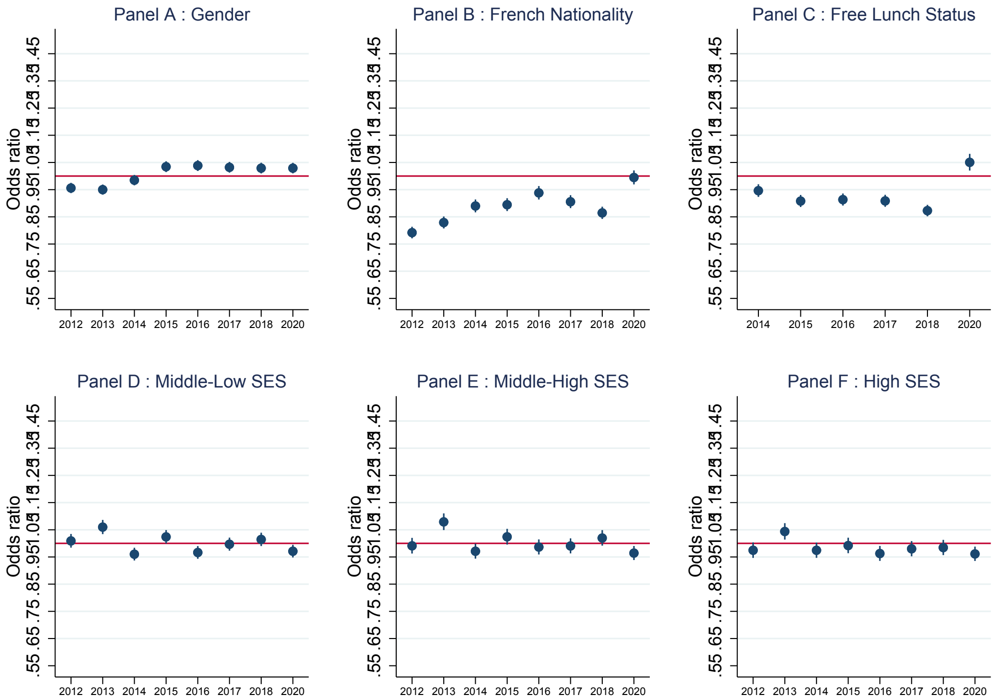
- Labor market area ("*Zone d'emploi*"): : An employment zone (or labor market area) is a geographic unit whose boundaries are chosen to delimit an area that includes both the workplace and the residence of the majority of a local labor force. INSEE divides France into 306 employment zones, which are used to study local labor markets, and are the territorial unit for which localized employment and unemployment rates are calculated. The division of employment zones covers both metropolitan France and the French overseas departments. The latest classification is based on commuting patterns observed during the 2016 census. The algorithm used to divide the country into employment zones is the Eurostats-recommended open source tool LabourMarketAreas.

  https://www.insee.fr/fr/information/4652957

Appendix B Heterogeneity Analysis

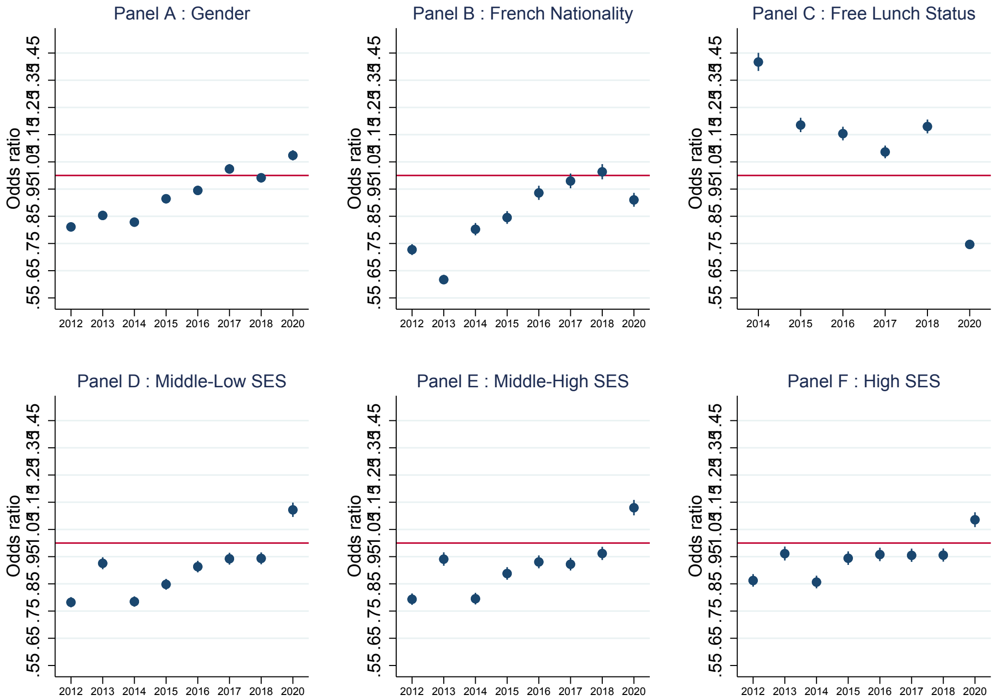
B.1 Demographics and Educational Outcomes

Figure B1: Heterogeneity in the Likelihood of Graduation



Notes: The figure presents the heterogeneity analysis based on a logit model (Equation 3). We cluster standard errors at the university level. The dependent variable in focus is the likelihood of graduating. The coefficient shown in the graph represents the odds ratio for the interaction term between the demographic category and the year. The reference year is the one preceding the pandemic. An odds ratio that does not overlap with the red horizontal line indicates a significant change in the likelihood of graduation for members of the corresponding demographic during the pandemic. We compute the equation once and plot the relevant parameter for each group on a separate panel to enhance readability.

Figure B2: Heterogeneity on Exam Attendance



Notes: The figure presents the heterogeneity analysis based on a logit model (Equation 3). We cluster standard errors at the university level. The dependent variable in focus is the exam attendance rate. The coefficient shown in the graph represents the odds ratio for the interaction term between the demographic category and the year. The reference year is the one preceding the pandemic. An odds ratio that overlaps with the red horizontal line indicates a significant change in the likelihood of exam attendance out for members of the corresponding demographic during the pandemic. We compute the equation once and plot the relevant parameter for each group on a separate panel to enhance readability.

B.2 Additional Analysis for International Students

Table B1: Impact of COVID-19 on Non-exchange Students

Panel A. Enrollment

	Overall (1)	Non-STEM (2)	Soft-STEM (3)	Hard-STEM (4)	UG (5)	G (6)	Ph.D. (7)
2020	0.886***	0.890***	0.900***	0.883***	0.826***	0.981	0.931
	(0.011)	(0.011)	(0.022)	(0.016)	(0.010)	(0.019)	(0.080)
Observations	12,221,071	6,835,965	2,371,537	3,012,897	7,516,548	4,092,012	400,802
Log Likelihood	-6,947,914	-4,013,758	-1,182,900	-1,691,500	-4,084,914	-2,468,507	-228,570.52

Panel B. Graduation

	Overall (1)	Non-STEM (2)	Soft-STEM (3)	Hard-STEM (4)	UG (5)	G (6)
2020	0.910***	0.896***	0.896	0.841***	0.841***	1.004
	(0.017)	(0.024)	(0.064)	(0.024)	(0.022)	(0.021)
Observations	3,562,944	2,146,510	530,574	885,779	2,056,116	1,506,650
Log Likelihood	-2,129,737	-1,149,440	-325,547.32	-505,211.47	-1,195,177	-894,740.7

Panel C. Attendance

	(1) Overall	(2) Non-STEM	(3) Soft-STEM	(4) Hard-STEM	(5) UG	(6) G
2020	1.057	1.114***	1.020	0.985	1.178**	1.152***
	(0.045)	(0.025)	(0.201)	(0.057)	(0.085)	(0.051)
Observations	10,087,252	6,102,360	1,359,961	2,623,936	1,825,346	1,306,251
Log Likelihood	-3,066,145	-1,873,459	-287,770.98	-848,989.45	-372,232.94	-349,962.44

Notes: The table replicates the analysis carried out in Tables 2 and 3 for the subset of students not enrolled as international students. The estimates are based on a logit model with university fixed effects and standard errors clustered at the university level. Panel A presents the analysis on the probability of re-enrollment for the upcoming academic year, panel B on the probability of graduation, and panel C on the likelihood of attending at least one exam.

B.3 Population Characteristics between Zones

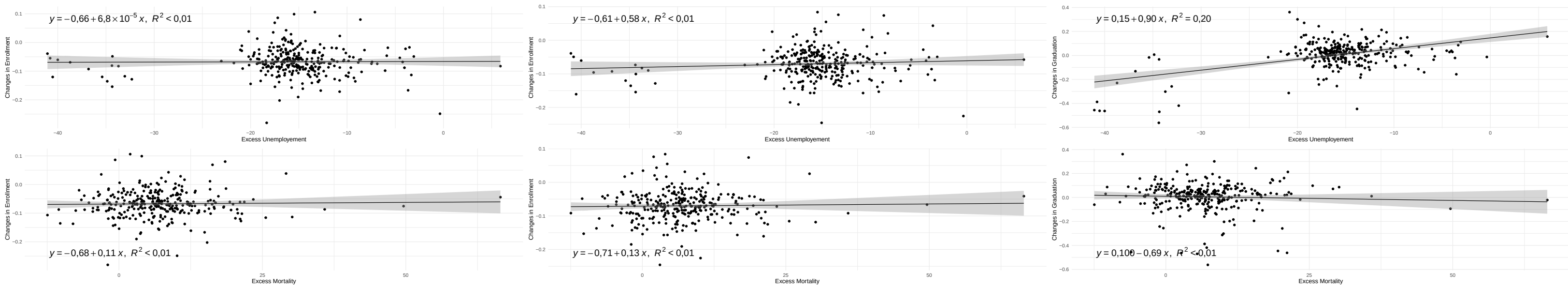
Table B2: Cohort Composition of Red and Green Zones in 2020

	Green zone	Red zone	Difference
Academic year 2019-2020			
Female	0.588	0.589	-0.000
Low SES	0.231	0.231	0.000
Middle Low SES	0.216	0.236	-0.020***
Middle High SES	0.205	0.202	0.003***
High SES	0.348	0.332	0.017***
French nationality	1.132	1.122	0.010***
Free Lunch Status	0.218	0.223	-0.005***

Notes: Each row presents the average proportion of students studying in red and green zones during the 2019-2020 academic year the categories listed on the left. Column (1) represents the cohort studying in the green zone during the first COVID-19 lockdown extension period, and column (2) represents the characteristics of the cohort in the red zone. Column (3) presents the difference in means using a two-tailed t-test, and asterisks indicate traditional levels of statistical significance (***, **, *, for 0.01, 0.05, 0.1, respectively).

Appendix C Potential Mechanisms and Alternative Measure

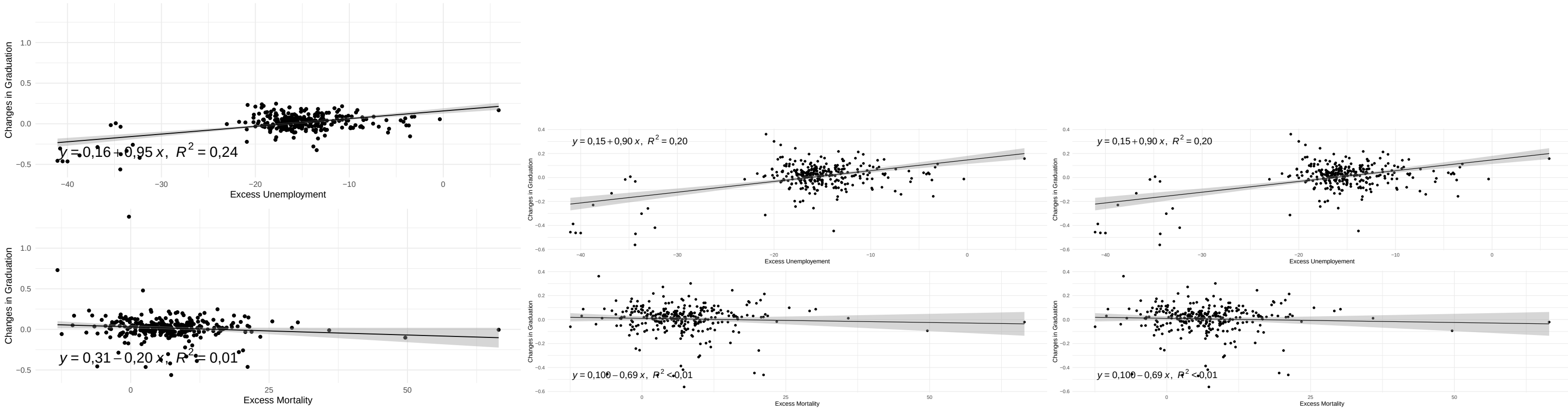
Figure C1: Potential Mechanisms and Enrollment Rate



(a) University's Location (b) Student's Location (c) Parents' Location

Notes: The figure illustrates the correlation between students' locations and the two mechanisms of interest. The dependent variable measures the disparity in re-enrollment behaviors between the year affected by the COVID-19 pandemic and the baseline period spanning from 2012 to 2020. The upper panel in each column depicts the connection between this variable and excess unemployment during the pandemic year. All measurements are conducted at the employment zone level. The displayed equation represents a univariate OLS regression. All locations are defined at the employment zone level: (a) the employment zone where the university is situated, (b) that of the reported residence of the student, and (c) that of the reported residence of the student's parents.

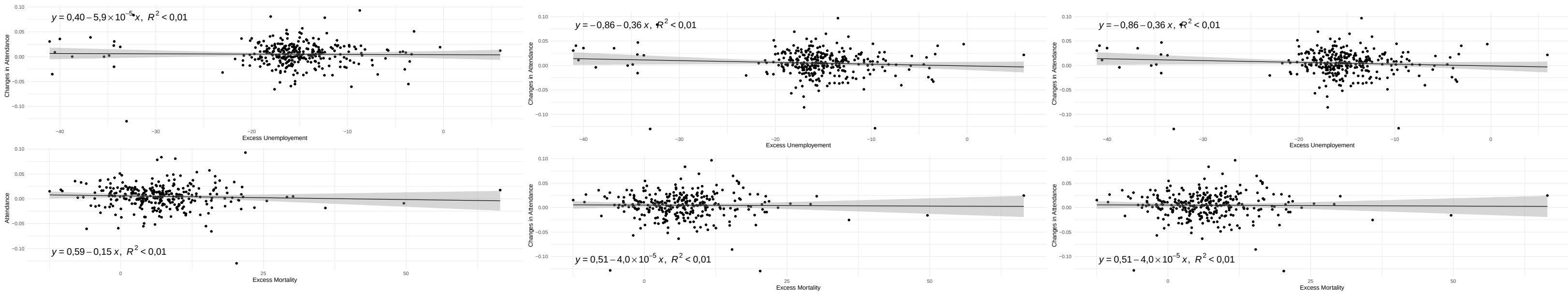
Figure C2: Potential Mechanisms and Graduation rate



(a) University's Location (b) Student's Location (c) Parents' Location

Notes: The figure illustrates the correlation between students' locations and the two mechanisms of interest. The dependent variable measures the disparity in graduation rate between the year affected by the COVID-19 pandemic and the baseline period spanning from 2012 to 2020. The upper panel in each column depicts the connection between this variable and excess unemployment during the pandemic year. All measurements are conducted at the employment zone level. The displayed equation represents a univariate OLS regression. All locations are defined at the employment zone level: (a) the employment zone where the university is situated, (b) that of the reported residence of the student, and (c) that of the reported residence of the student's parents.

Figure C3: Potential Mechanisms and Attendance Rate



(a) University's Location (b) Student's Location (c) Parents' Location

Notes: The figure illustrates the correlation between students' locations and the two mechanisms of interest. The dependent variable measures the disparity in exam attendance rate between the year affected by the COVID-19 pandemic and the baseline period spanning from 2012 to 2020. The upper panel in each column depicts the connection between this variable and excess unemployment during the pandemic year. All measurements are conducted at the employment zone level. The displayed equation represents a univariate OLS regression. All locations are defined at the employment zone level: (a) the employment zone where the university is situated, (b) that of the reported residence of the student, and (c) that of the reported residence of the student's parents.

Appendix D Robustness Checks

D.1 Difference-in-differences without Ile-de-France

Table D1: Did without Ile-de-France

Panel A. Enrollment

	2013 to 2019 (1)	2013 to 2019 (2)	2019 (3)	2018 to 2019 (4)	2017 to 2019 (5)
2020	0.854***	0.855***	0.906***	0.900***	0.904***
	(0.010)	(0.009)	(0.010)	(0.009)	(0.010)
Red	1.067*	1.157***	1.128*	1.141**	1.152***
	(0.039)	(0.056)	(0.072)	(0.067)	(0.063)
2020 × Red	1.007	1.005	0.993	0.995	0.994
	(0.029)	(0.029)	(0.030)	(0.025)	(0.025)
Constant	3.509***	3.463***	2.372***	2.485***	2.536***
	(0.130)	(0.102)	(0.080)	(0.081)	(0.079)
Fixed effects	No	Yes	Yes	Yes	Yes
Observations	9,802,738	9,802,535	2,354,538	3,462,641	4,597,523
Log Likelihood	-5,614,588	-5,595,280	-1,397,270	-2,031,741	-2,686,386

Panel B. Graduation

	2013 to 2019 (1)	2013 to 2019 (2)	2019 (3)	2018 to 2019 (4)	2017 to 2019 (5)
2020	1.117***	1.102***	0.951**	1.010	1.030
	(0.029)	(0.028)	(0.024)	(0.019)	(0.022)
Red	0.841***	0.980	1.063	1.022	0.998
	(0.048)	(0.033)	(0.055)	(0.052)	(0.046)
2020 × Red	1.023	0.996	0.976	0.993	1.024
	(0.065)	(0.053)	(0.034)	(0.036)	(0.045)
Constant	2.433***	2.193***	1.855***	2.098***	2.104***
	(0.187)	(0.108)	(0.112)	(0.119)	(0.115)
Fixed effects	No	Yes	Yes	Yes	Yes
Observations	2,895,881	2,895,728	717,280	1,049,899	1,380,076
Log Likelihood	-1,755,701	-1,726,732	-410,225.57	-608,581.19	-805,766.19

Panel C. Attendance

	2013 to 2019 (1)	2013 to 2019 (2)	2019 (3)	2018 to 2019 (4)	2017 to 2019 (5)
2020	1.106**	1.121***	1.067***	1.125***	1.144***
	(0.049)	(0.049)	(0.021)	(0.038)	(0.035)
Red	0.896	1.096*	1.035	1.066	1.062
	(0.085)	(0.057)	(0.069)	(0.067)	(0.058)
2020 × red	1.018	1.074	1.054	1.028	1.045
	(0.070)	(0.077)	(0.049)	(0.067)	(0.055)
Fixed effects	No	Yes	Yes	Yes	Yes
Observations	8,066,794	8,066,269	1,993,533	2,961,547	3,881,304

Notes: This table reports estimates of likelihood of re-enrolling for the following year, graduating, and exam attendance relative to a control period, for individuals under a more stringent COVID-19 policy regime (i.e. red zone) during the first lockdown extension period. For panels A C, the sample covers all students enrolled university degree in France from 2012 to 2021. For panel B, the sample consists of all students enrolled in a graduation year from 2012 to 2021. Each column presents a logit regression performed separately for a given control group time window. The regression includes university fixed effects (to account for differences in university quality) and the student characteristics listed in Table 1. Standard errors (shown in parentheses) are adjusted for clustering at the university level . Asterisks indicate traditional levels of statistical significance (***, **, *, for 0.01, 0.05, 0.1, respectively).

D.2 Falsification Test

Table D2: Difference-in-differences: Falsification Test

Panel A. Enrollment

	2012 to 2018 (1)	2017 to 2018 (2)	2016 to 2018 (3)	2015 to 2018 (4)	2014 to 2018 (5)
2018	0.923***	1.016	0.997	0.979**	0.965***
	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
Red	1.054*	1.148***	1.147***	1.146***	1.149***
	(0.032)	(0.042)	(0.040)	(0.038)	(0.038)
2018 × red	1.007	1.007	1.005	1.009	1.012
	(0.020)	(0.020)	(0.019)	(0.017)	(0.017)
Fixed effects	No	Yes	Yes	Yes	Yes
Observations	8,109,939	2,862,593	4,292,078	5,678,436	7,008,610
Log Likelihood	-4,578,638	-1,647,837	-2,464,233	-3,246,525	-3,991,534

Panel B. Graduation

	2012 to 2018 (1)	2017 to 2018 (2)	2016 to 2018 (3)	2015 to 2018 (4)	2014 to 2018 (5)
2018	1.067***	0.991	1.009	1.029*	1.038**
	(0.021)	(0.016)	(0.017)	(0.017)	(0.017)
Red	0.894**	0.985	0.992	1.006	1.010
	(0.046)	(0.039)	(0.035)	(0.032)	(0.030)
2018 × red	1.031	1.070*	1.059	1.041	1.032
	(0.042)	(0.041)	(0.043)	(0.040)	(0.037)
Fixed effects	No	Yes	Yes	Yes	Yes
Observations	2,370,582	850,647	1,264,737	1,667,928	2,059,773
Log Likelihood	-1,466,458	-507,024.87	-756,016.94	-1,002,209	-1,240,775

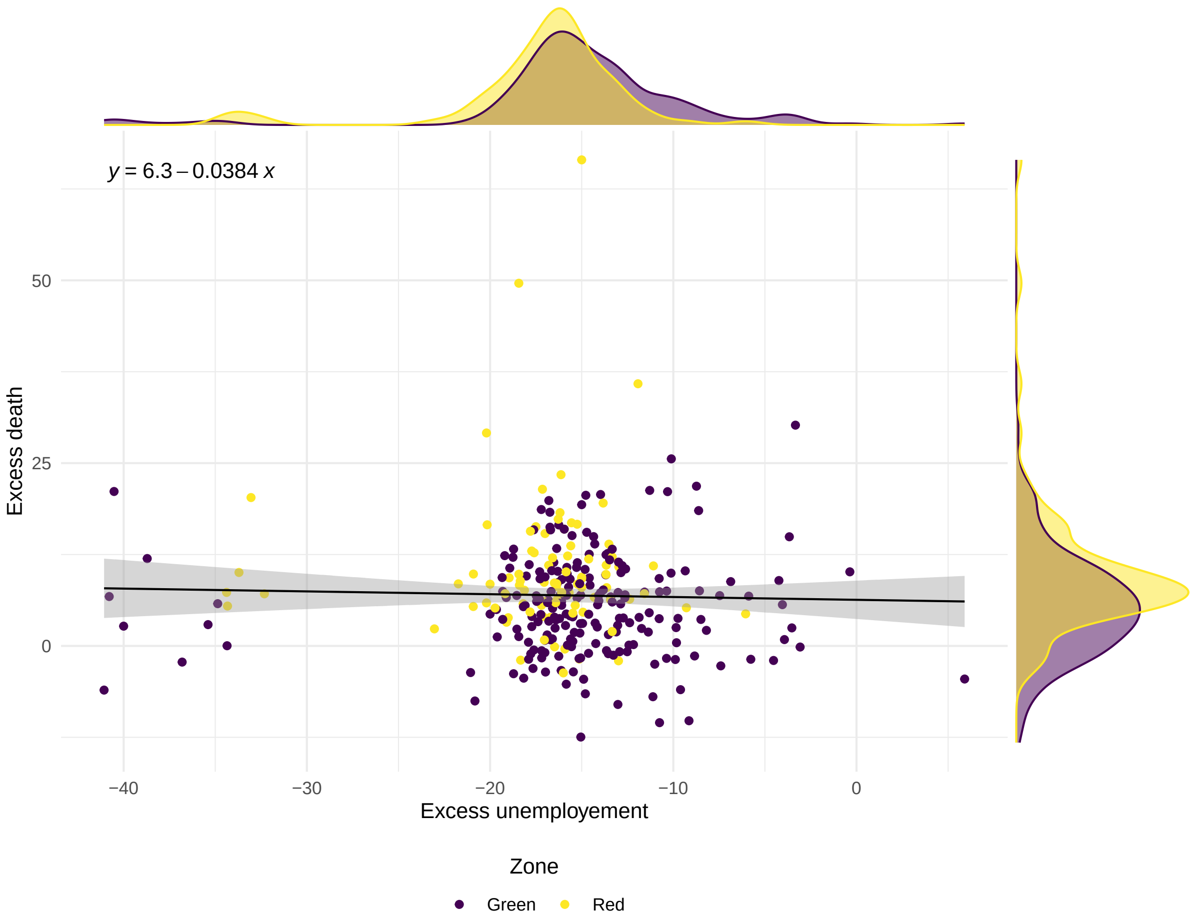
Panel C. Attendance

	2012 to 2018 (1)	2017 to 2018 (2)	2016 to 2018 (3)	2015 to 2018 (4)	2014 to 2018 (5)
2018	0.950	1.018	1.038	1.022	0.980
	(0.047)	(0.043)	(0.047)	(0.039)	(0.037)
Red	0.835**	1.109*	1.115**	1.126***	1.116***
	(0.063)	(0.060)	(0.049)	(0.044)	(0.042)
2018 × red	1.082	1.065	1.062	1.074	1.120*
	(0.098)	(0.064)	(0.065)	(0.061)	(0.067)
Fixed effects	No	Yes	Yes	Yes	Yes
Observations	6,521,296	1,169,284	2,294,061	3,396,148	4,466,925
Log Likelihood	-2,050,269	-366,676.51	-722,082.13	-1,059,809	-1,363,226

Notes: This table reports placebo estimates of likelihood of re-enrolling for the following year, graduating, and attending at least one exam whether individuals are impacted by more stringent policy (i.e. red zone) relative to students over various control periods. The false-treatment group presented here is the 2018-2019 cohort. For panel A, the sample covers all students enrolled in a university degree in France from 2012 to 2020. For panel B, the sample includes all students enrolled in a graduation year. Each column presents a logit regression performed separately with given control group time window. The regression includes university fixed effects (to account for differences in university quality) and the student characteristics listed in Table 1. Standard errors (shown in parentheses) are adjusted for clustering at the university level. Asterisks indicate traditional levels of statistical significance (***, **, *, for 0.01, 0.05, 0.1, respectively).

Appendix E Relationship between our Two Mechanisms

Figure E1: Changes in Unemployment and Mortality



Notes: The figure portrays the relationship between excess unemployment and excess mortality, as measured at the employment zone level against their 2012-2020 baseline rates. Within the panel, each data point represents an observation. The line represents a univariate linear regression on data from all employment zones, along with a 95% confidence interval in gray. The equation for this linear regression is presented in the upper-left quadrant of the plot. The datapoints were then differentiated according to whether the corresponding employment zone was situated in the green or red zones during the second lockdown phase in France in 2020: the red zone is indicated by the darker shade of purple, while the green zone is depicted in the lightest shade of yellow. The distribution of each variable is represented along its respective axis .